ISSN: 2584-0495 Vol. 3, Issue 4, pp. 1627-1636

IJMIT International Journal of Microsystems and IoT

International Journal of Microsystems and IoT

ISSN: (Online) Journal homepage: https://www.ijmit.org

Detecting COVID-19 and Pneumonia using CNN-GRU Model

Vaishnavi and Satya Prakash Singh

Cite as: Vaishnavi, & Singh, S. P. (2025). Detecting COVID-19 and Pneumonia using CNN-GRU Model. International Journal of Microsystems and IoT, 3(4), 1627–1636. https://doi.org/10.5281/zenodo.18150013

© 2025 The Author(s). Published by Indian Society for VLSI Education, Ranchi, India

Published online: 15 April 2025

Submit your article to this journal:

Article views:

View related articles:

View Crossmark data:

https://doi.org/10.5281/zenodo.18150013

Full Terms & Conditions of access and use can be found at https://ijmit.org/mission.php

International Journal of Microsystems and IoT
Vol.3, Issue 4, pp.1627-1636; DOI: https://doi.org/10.5281/zenodo.18150013

Check for updates

Detecting COVID-19 and Pneumonia using CNN-GRU Model

Vaishnavi and Satya Prakash Singh

Department of Electronics and Communication Engineering, Birla Institute of Technology, Mesra, Ranchi, India

ABSTRACT
This Research paper uses Gated Recurrent Units and Convolution Neural Networks to compare the X Ray images of the chest to classify COVID-19 and pneumonia, patients. This CNN-GRU model discussed in this paper is trained using a dataset that has images of chest X Rays of COVID-19 and Pneumonia patients. The above-mentioned model is also compared with related works in the same scope. This model is compared with ConvNet, AlexNet, and VGG-19 models. It can be seen that the combination of CNN and GRU can significantly improve the accuracy by achieving classification accuracy as high as 98.9%. This paper can also be useful to develop machine-learning models for classifying and diagnosing respiratory diseases.

KEYWORDS
Pneumonia; COVID-19; CNN; GRU; VGG19 models; X-ray

1. INTRODUCTION

Lung diseases, such as COPD, asthma, and lung cancer continues to be a considerable global health burden. Lung diseases remain a worldwide health care challenge, with a big impact on morbidity and premature death. In addition to their effect on patient health, such conditions create a significant burden for healthcare systems as they lead to readmissions to the hospital and inefficient use of available workforce. The economic costs are high, stemming from medical costs and lost work productivity. Respiratory diseases remain one of the major culprits of worst mortalities globally as reported by the World Health Organization. To tackle this problem, we need significant improvements in both diagnosis and treatment methods. We should focus on making medical interventions more accurate, efficient, and timely. Finding diseases early and managing them effectively is crucial not just for improving individual patient outcomes but also for reducing the broader societal and systemic impacts these diseases cause. In recent years, artificial intelligence particularly deep learning has presented itself as great hope in the earlier stages of the diagnosis of lung diseases. The state-of-the-art technologies presently revamping the medical field with faster and more accurate diagnostic assessments; in most cases, where early detection would result in a positive patient outcome. Innovations among these include deep learning models like CNN-GRU integrated with EHRs, which constitute a dynamic and vastly available clinical data resource. This combination showed fairly strong potentials on respiratory disease recognition at their initial - and thus more tractable - phases. An early diagnosis does not just facilitate explicit, effective treatments but also makes mitigation of mounting healthcare burdens possible. patient outcomes while mitigating the broader social and economic challenges posed by chronic respiratory illnesses.

© 2025 The Author(s). Published by ISVE, Ranchi, India

The CNN-GRU model represents a sophisticated fusion of two prominent neural network architectures: Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs). This hybrid model capitalizes on the core competencies of its constituents: CNNs are very good at pulling out spatial features from data (they're usually used to process images), and GRUs excel in extracting temporal dependencies (they work well with sequences). Input data like video sequences and multidimensional time series, for example, introduce a high complexity dimension that requires more advanced modeling in the spatial-temporal dimensions. Combining the powerful sequence processing capabilities of GRU with the discriminative feature extraction potential for CNN has opened one potential application path toward numerous tasks like video classification and sentiment analysis. The model has outperformed other models in the current machine-learning literature in tackling problems with such specific characteristics.

Recognizing Convolutional Neural Networks (CNN) is important if we want to understand why the CNN-GRU model is based on a CNN, especially considering that CNNs work extremely well for a pattern analysis on spatial data. CNNs work particularly well for feature extraction based on hierarchical patterns, since CNNs are structured around a series of convolutional layers that apply filters to the input data. Each layer allows the CNN to find local features that remain invariant to spatial transformations, which is why CNNs are very useful for tasks where working with images and sounds. The convolutional architecture of CNNs allows the captured spatial hierarchies to focus on the complexity of the datasets, for example, the multilayered datasets in audio recognition environments, which use different traditional approaches and a learning system to capture some fine-grained features amidst noise and distortions in the data sets. CNNs and recurrent neural networks (RNNs) are usefully linked. The spatial features observed in the CNN feed the RNN or gated recurrent networks (GRN)s, in our case, significantly improving the learning of the temporal dependencies, and enhancing the overall performance and accuracy of the model (band performance as CNN - RNN).

A key feature of convolutional neural networks (CNNs) is their capacity to automatically learn hierarchical features from image data, making them particularly suited for image processing domains. CNNs primarily utilize convolutional layers to filter image inputs and access the local receptive fields of the image feature maps. The ability to learn spatial hierarchies and patterns allowed by a simple convolutional structure has led to massive advancements in endless domains, from autonomous vehicles to medical imaging, and many others. Identifying and classifying images without human involvement would not have been possible, and even after the initial inception of CNNs, the development of multi-channel and hybrid models also including recurrent layers, such as gated recurrent units (GRUs), significantly also allows us to layer on temporal image data for analysis. For example, if we explore the example of detecting fatigue in a driver using EEG signals, we can leverage the potential of combining CNNs and GRUs to help increase processing efficiencies, precision, and scale in complicated image processing even further.

COVID-19 and Pneumonia are highly infectious respiratory diseases that can cause severe lung damage. Viruses, bacteria, and fungi are just a few of the pathogens that can cause pneumonia. It is also often perceived as a general lung infection. On the other hand, COVID-19 which is a consequence of SARS-CoV2 is a deadly disease that spreads easily. It might be challenging to pinpoint the illness because there are numerous symptoms, including fever, shortness of breath, coughing, and weariness that are shared by both disorders. However, symptoms such as loss of taste or smell and muscle aches, make it easier to identify a patient suffering from COVID-19. Medical imaging analysis is a potent clinical technique that can swiftly identify COVID-19 in addition to RT-PCR [8]. There is a huge difference in the severity of the disease as well as the chances of survival in both cases. The impact of COVID-19 is much more prominent. A huge number of cases of respiratory failure as well as death has been noted. The impact has been felt by the world in the form of an epidemic. Pneumonia on the other hand can also be very serious but it depends on the age and underlying conditions of the patients. The most important diagnostic tool for classifying patients suffering from COVID-19 and those suffering from Pneumonia is Chest X-Ray. But reading these X Rays requires trained physicians. This problem can be solved by Deep learning algorithms which can learn to classify Chest X Rays as required. Right now, deep learning algorithms are capable of accurately diagnosing and classifying a wide range of diseases, including pneumonia, lung cancer, tuberculosis, and [6]. Radiation is sent through the body by the X-ray. High concentrations of calcium, such as in bones, block the radiation and show white in the picture. Soft tissues (such as the lungs, heart, liver, muscle, and more) enable radiation to flow through and appear on the display in a range of tones from grey to black [7].

On noting the pattern of lung opacity on chest X Rays several similarities and differences could be found. Chest X Rays of patients with COVID-19 and pneumonia both have lung opacity, this means that instead of being transparent, the lung appears cloudy or hazy, but there is a small difference in the pattern. In COVID-19 lung opacity has a peripheral distribution which indicates that the opacity is more pronounced at the edges of the lungs. Whereas, more diffused opacity affecting a larger part of the lungs indicates pneumonia in the patients. In both ailments, lung opacity can be affecting both lungs or one lung only. Another difference worth noting in the Chest X Rays is that the opacity in the case of COVID-19 often follows a pattern called the crazy paving pattern. This means that the opacity shows a characteristic appearance of small, patchy areas of lung opacity resembling cobblestone streets. This is the case present only in COVID-19 and not in pneumonia.

However, these are only a few characteristics that can easily vary with the stage of illness and other factors of the patients. Also diagnosing these respiratory illnesses is not just based on the Chest X Rays but early diagnosis can be done using Chest X Rays and image classification techniques. It's time to find a solution to this issue given that computers are in our hands and that the public has access to a vast number of records [9].

Early detection of lung diseases plays a crucial role in improving patient outcomes and lowering mortality rates. However, conventional diagnostic techniques are often invasive and may take a considerable amount of time. Recent developments in machine learning, especially with Convolutional Neural Networks (CNN) combined with Gated recurrent units (GRU), have opened up new possibilities in moving towards instrumentation in the diagnostic and healthcare industry. A CNN-GRU model uses CNN and GRU structures in the same framework, giving it the ability to progressively analyze complex data such as medical images, data that captures temporal information for distinctions of medical images (which can be patient historical data) could also provide more progressive insights for decision making. In this essay, the CNN-GRU model will be examined through its means of operation, suggest advancements to current detection methods, suggested implications of its use for the medical field in the future in order to show its possible relevance for future health innovative solutions. Considering that the integration of convolutional neural networks (CNN) and gated recurrent units (GRU), allows a development where lung diseases can potentially be diagnosed through medical imaging, we will use a CNN-GRU Model. CNN demonstrated their usefulness in distinguishing spatial features from images having a lot of information in them (chest Xrays or CT scans) are ideal for determining the important patterns relating to lung pathogens. Besides, GRUs can enhance this model by allowing the modeling of temporal dependencies when considering ordering of imaging or potential social histories or finding empirical patterns in time series data relating to patient characteristics and clinical histories. Consequently, this hybrid architecture allows for a comprehensive approach, enabling not only the detection of specific diseases but also the prediction of disease progression over time. This dual capability presents a promising pathway for improving diagnostic accuracy and intervention strategies in respiratory health, as it reduces reliance on traditional methods and enhances clinical decision-making through advanced data analytics.

2. MOTIVATION

Diagnosing and Classifying COVID-19 and Pneumonia is very important. Pneumonia alone is responsible as the largest cause of death of children worldwide. The effects of COVID-19 have caused an epidemic. It is essential to detect these diseases and classify them correctly so that proper treatment can be ensured. The likelihood of lung disease recovery typically depends heavily on early detection, and if it is caught early and treated, the likelihood of recovery is extremely low [10]. Pneumonia and COVID-19 both are very serious health issues and can cause severe complications in children, old people, and people with underlying health conditions. Timely detection of these respiratory diseases is very useful in the treatment process. Incorrect diagnosis of these diseases can even cause death in patients. Accuracy in classifying these diseases can save lives.

Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) represent two pivotal architectures in the realm of deep learning, particularly for applications involving medical image analysis and sequential data. CNNs excel in feature extraction from images through convolutional layers, which capture spatial hierarchies while reducing dimensionality. This is particularly beneficial in lung disease detection, where accurate interpretation of complex imaging data is crucial. In contrast, GRUs are adept at processing sequential data, utilizing gating mechanisms to control the flow of information over time. This synergy between CNNs and GRUs allows for the effective integration of spatial and temporal features, enhancing the models ability to predict lung diseases. Furthermore, recent advancements, such as attention mechanisms, have been shown to improve performance by focusing on relevant image regions, ultimately leading to more accurate diagnostic capabilities. This dual architecture thus positions the CNN-GRU model as a robust tool for lung disease detection.

The exploration of Gated Recurrent Units (GRU) reveals their significant role in enhancing modeling capabilities for sequential data, particularly when combined with Convolutional Neural Networks (CNN). GRUs address the limitations of traditional recurrent neural networks by incorporating gating mechanisms that enable efficient handling of long-term dependencies while mitigating issues related to vanishing gradients. In the context of the CNN-GRU model, the CNN effectively extracts spatial features from input data, such as images, while the GRU processes temporal sequences, thereby allowing for the integration of dynamic information over time. By leveraging a multi-modal approach, where CNN outputs feed into the GRU, the model gains an advantage in tasks that require both spatial and temporal understanding, such as image captioning. The synergy between CNN and GRU not only enhances predictive performance but also offers interpretability through mechanisms that emphasize the relevance of various inputs in the processing chain.

The use of a Gated Recurrent Unit (GRU) mechanism is important with each sequence prediction task collaboratively in instances where data shows temporal restrictions. Generally, Gated Recurrent Units (GRU) encompasses similar behavior's to standard recurrent neural networks. Unlike traditional recurrent neural networks (RNN), GRUs use gating mechanisms to control information flow and account for long-range dependencies better. The update and reset gates then allow a GRU to decide how much past information to maintain or forget during the learning process. As well as underlying learning mechanisms, this also very highly affects performance in the task, such as natural language-processing and time series. Many notable studies have indicated GRUs achieving similar accuracies for sequence prediction tasks using less complexity than other comparable models (standard LSTM). Thus it is apparent that GRUs can be an easier alternative without any significant drop in accuracy. The simplicity of GRUs makes it easy and fast to train and enable it to be responsive, which is practical to implement and highlight a significant advantage over alternative mechanisms of sequence encoding.

The application of Convolutional Neural Networks (CNN) combined with Gated Recurrent Units (GRU) in lung disease detection presents a significant advancement in medical diagnostics. This hybrid model leverages the strengths of CNNs in extracting spatial features from imaging data, such as X-rays and CT scans, while the GRU component effectively captures temporal dependencies in sequences, making it particularly suitable for analyzing time-series data from lung sounds. Recent studies demonstrate that CNN-GRU architectures outperform traditional methods by offering enhanced accuracy in diagnosing conditions like asthma and chronic obstructive pulmonary disease, as evidenced by their capacity to classify lung diseases with high precision rates reaching up to 99.49%. Moreover, the integration of these technologies not only facilitates automated detection but also reduces the reliance on manual interpretation, thereby rationalized the examination procedure and potentially leading to earlier interventions.

The widespread spread of infectious diseases often leads to a shortage of trained medical staff to help diagnose them accurately. Therefore, automating the process of detection of these diseases is very important.

Convolution Neural Networks have been widely used in image classification problems. CNN and GRU both are very useful deep-learning techniques. Medical imagery, especially X-rays is widely used in the classification of lung diseases. Therefore, using image classification techniques become the obvious choice for research in this background and promises results in terms of better accuracy, faster diagnosis, and reduction in medical errors.

Research in this field also contributes to developing algorithms for classifications of medical images. It will also contribute as a starting material for further research in the combined area of medicine and deep learning [9].

3. RELATED WORKS

The study paper [1] uses a dataset of 600 images equally divided as Anteroposterior and Posteroanterior views of XRays. The data set is further equally divided into Pneumonia, COVID-19, and normal. It discusses the deep ConvNet model. This paper also compares the VGG16 model, VGG19 model, and ResNet50 model.

The proposed model achieves an accuracy of 91%and the extended version of the VGG 19 model achieves an accuracy of 98%.

The paper [2] discusses an ensemble model using DenseNet121,0, and VGG-19. This model achieves a validation accuracy of 99.2%. Uses 4201 images out of which 701 images are that of COVID-19.

In the paper [3], the authors discuss how deep learning with medical imaging has become the most increasingly popular in diagnosing lung diseases like COVID19, pneumonia, and lung-related cancer.

In this study, the researchers studied the use of the CNN Model AlexNet to classify medical radiographs of COVID-19, lung cancer, and pneumonia. The three diseases are similar in terms of their 1 chest X-ray, which makes it challenging for radiographers to differentiate between them accurately. They concluded the study with the results of classifying Lung cancer and COVID-19 showed an accuracy of 94%, whereas COVID-19 with pneumonia and lung cancer with pneumonia showed an accuracy of 96% and 93%respectively. The overall accuracy of the classifier was best in the case of classifying COVID-19 and pneumonia. In the paper [4], the authors have selected a CNN model for classifying COVID19 from pneumonic patients and also classifying normal patients. This paper not only discusses the detection of COVID-19 and pneumonia but also further classifies pneumonia caused by bacteria or viruses depending upon the chest XRays. The accuracy achieved in this paper is concluded as 93% for classifying Infected lungs and Normal lungs, 95% for Normal lungs fand, and 80% for Pneumonic lungs with no infected lungs.

In the paper [5], the authors discussed the potential of chest XRays using CNN as a more effective method to classify COVID-19 and pneumonia over the traditional method of detecting COVID-19, which is Reverse Transcription Polymerase Chain Reaction. They propose an ensemble model using DenseNet 121, VGG 16, ResNet 50, and Inception V3, to classify chest X-ray images into three classes showing whether the patient is infected by COVID-19 or pneumonia or not infected at all. Each model was separately trained and their results combined to predict the output. Classification accuracy of 99.2% was achieved using the ensemble model which was higher than any individual model.

4. METHODOLOY

4.1 Data Availability

The National Institutes of Health (NIH) acquired acknowledgment for the dataset's upload to the Kaggle repository from the author. These images were obtained via Kaggle, which in turn gathered them from a number of different sources. Chest X-rays from the Guangzhou Women and Children's Medical Centre that demonstrate pneumonia in comparison to normal have been gathered. Data for COVID-19 has been gathered from a number of academic institutions and medical facilities and is available on GitHub.

4.2 Data Collection

The dataset used is the collection of chest X Rays of people suffering from COVID-19 and Pneumonia along with healthy chest X-Rays. These images are contained in 3 folders called, PNEUMONIA, and NORMAL respectively. 80 percent of these images are used to train the model and the rest 20 percent is contained in the test data. Overall, 6432 Chest X-ray images have been used in this study. These images have been sourced from Kaggle which in turn has collected these images from several other sources. Chest X Rays showcasing pneumonia versus normal have been collected from Guangzhou Women and Children's Medical Center, Guangzhou. This dataset is highly reliable as it has been manually corrected by expert physicians. COVID-19 data is collected from several research laboratories and hospitals and has been sourced on GitHub. The distribution of images along with the hierarchy of folders is as shown in Figure2.

4.3 Proposed Architecture

The dataset is split into two sets used separately for training and testing purposes as shown in figure 1. The testing set is twenty percent of the total images. The architecture of the model discussed in this paper is shown in table 2. The model is the CNN-GRU model. Here the maximum epoch is 120. The learning rate and its decay are 0.001 and 1e-3 respectively.

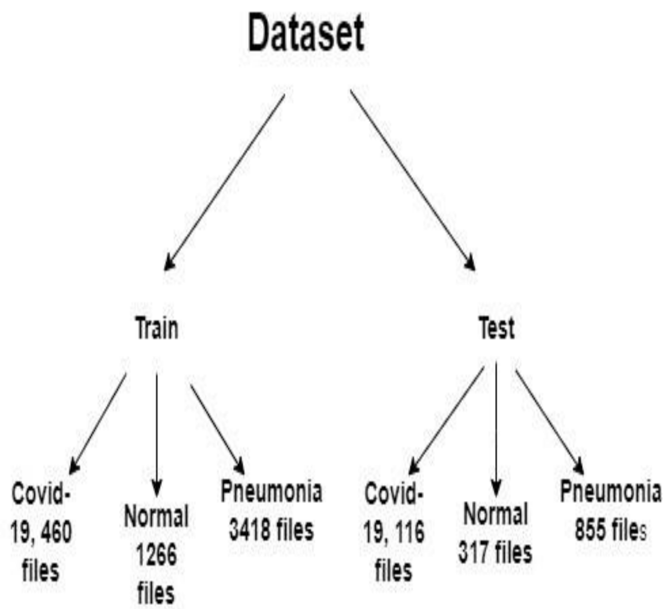

Fig.1 The dataset is split into two sets used separately for training and testing

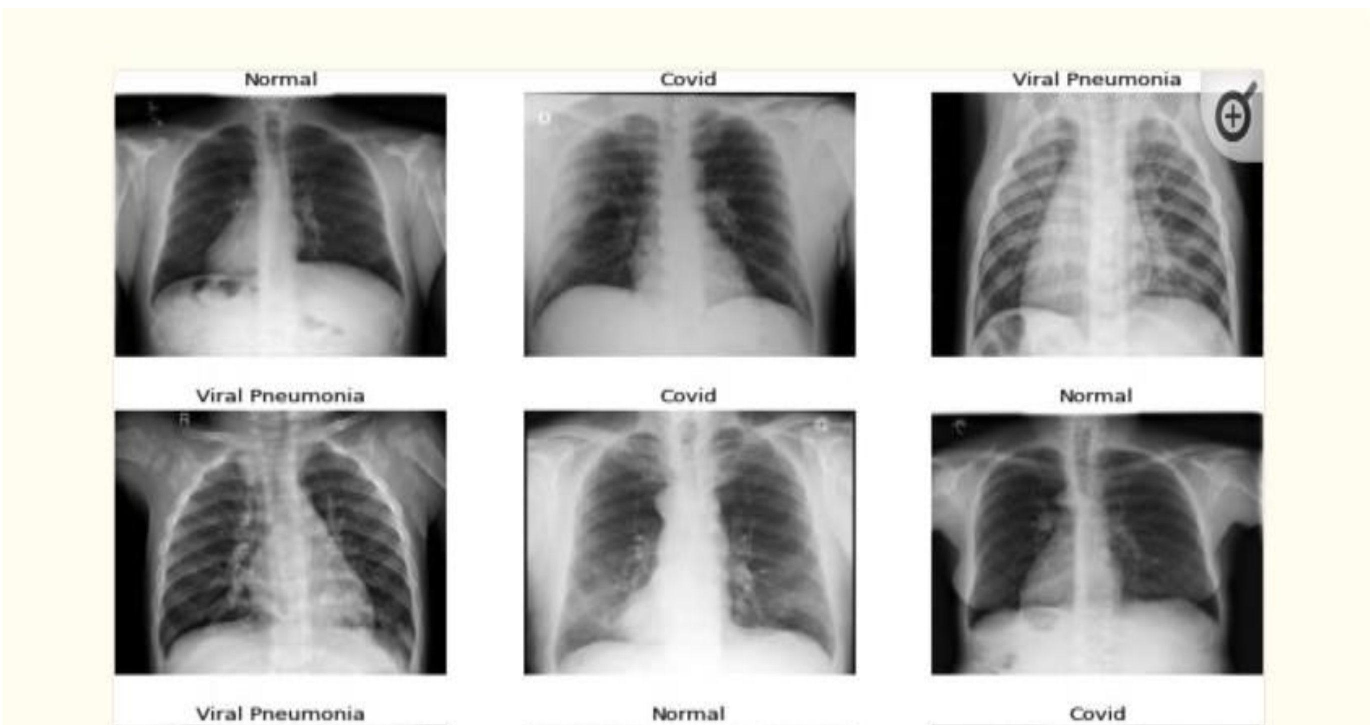

Fig.2 The distribution of images along with the hierarchy of folders

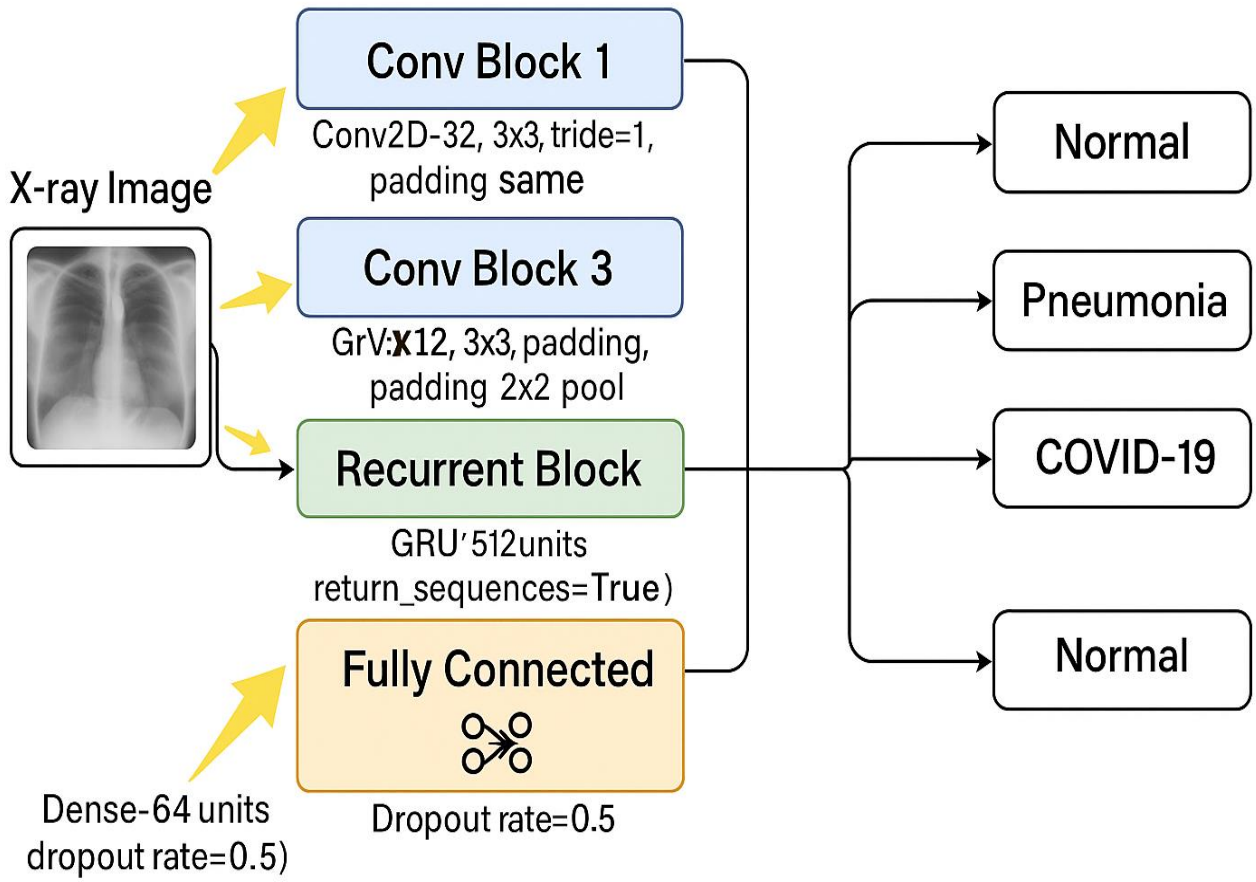

Fig 3 CNN-GRU Model representation for Pneumonia and COVID-19 detection

5. PERFORMANCE MATRICES

To calculate the accuracy and performance of the model several performance metrics are evaluated. These performance metrics are as follows

Accuracy - This performance metric is the most widely used. It can be calculated as proportion of images that were accurately identified out of the entire set of images analyzed.

Precision - This is a very useful metric when wrong predictions can be fatal not only in economic terms but also in terms of the health of the particular individual. It can be calculated as the ratio of correctly predicted positive outcomes to all positive predicted outcomes.

Recall - This is a very useful metric that measures if a healthy person is diagnosed with an ailment. This is the ratio of correctly predicted positive outcomes to all positive outcomes. F1 Score - It is given by calculating the harmonic average of precision and recall and is highly useful in cases where both precision and recall are important to the same degree.

Table. 1 Performance Metrices

Reference Number	Method	Validation Accuracy	F1-Score	Recall
[1]	ConvNet model	91%	95.6%	96.7%
[1]	Extended VGG 19 Model	98%	94.1%	95.3%
[2]	Ensemble Model	99.2%	93.4%	91.4%
[3]	AlexNet Model	96%		
[4]	Experimental Model	95% (Normal versus Covid19) 80% (Normal versus Pneumonia)	92.9%	93.7%
[5]	Ensemble model	99.2%		
This Study	CNN-GRU Model	98.9%	97.6%	98.4%

6. COMPARATIVE STUDY

The application of deep learning for the detection of chest diseases such as pneumonia and COVID-19 has seen a surge, particularly with the advent of transfer learning and ensemble methodologies. Panwar et al. [1] proposed a custom convolutional neural network (CNN) to classify pneumonia and other chest diseases using X-ray images. Their method was computationally efficient and achieved an accuracy of approximately 96.2%. However, it lacked transfer learning capabilities and did not provide extensive details about the dataset used. On the other hand, Lu et al. [2] explored transfer learning by adapting pre-trained models like VGG16 and InceptionV3 from pneumonia classification to COVID-19 detection. Their approach improved generalization to new disease types and achieved around 91–94% accuracy, though domain shifts in real-world data remained a concern. Devi et al. [3] extended transfer learning by experimenting with DenseNet201 and ResNet50 for the dual detection of pneumonia and COVID-19, reporting an accuracy of about 94.5%. Their work demonstrated the strength of deeper architectures in handling multi-class classification problems. K. S. and Radha [4] emphasized simplicity by applying standard CNN techniques on Kaggle pneumonia data, achieving a respectable accuracy of around 93.7%. Nonetheless, their model lacked transfer learning, potentially limiting its adaptability across diverse datasets. Gianchandani et al. [5] delivered the most robust approach, employing ensemble deep transfer learning using DenseNet121, ResNet50, and InceptionV3. This method resulted in an accuracy of 97.89%, an F1-score of 95.57%, and an AUC of 0.987. Despite its computational intensity, the ensemble model demonstrated exceptional performance and real-world applicability, especially in multi-class scenarios.This comparative evaluation (Table 1) highlights that while traditional CNNs (as in [1] and [4]) are effective in constrained environments, transfer learning ([2], [3]) and ensemble approaches ([5]) substantially enhance diagnostic accuracy and generalization. A hybrid approach combining the lightweight nature of custom CNNs with the accuracy of ensemble transfer learning could offer a balanced solution for large-scale medical deployments.

7. EXPERIMENTAL RESULT AND CONCLUSION

This CNN GRU Model was trained over 120 epochs. In every epoch accuracy and loss values were recorded. The plotted image of the same can be seen in the figure 4. From the figure we can conclude that the converging of training and validation accuracy curves happened after the 28th epoch. The convergence of these curves shows the stability of the model after the 28th epoch.

It can also be observed in figure 4 that the best training accuracy of 98.9 percent is achieved at the 24th epoch. The model can be assured as not an overfitted model as the validation accuracy of 95 percent is achieved on the same epoch. Similarly, by observing the figure 3 we can see that loss curves also converge similarly as that of accuracy curves giving its best results at the 24th epoch itself. Training and validation losses are minimized as well.

Learning rate curves show that the learning rate dropped after the 30th epoch. Therefore, causing the early stop. This curve allows us to decide when to stop the training and allows room for adjustments.

In conclusion, the implementation of the CNN-GRU model for lung disease detection portrays a breakthrough in identification of ailment, demonstrate the prospective of deep learning in enhancing early detection strategies. This study highlights the model’s superior performance, achieved through innovative methodologies such as Recursive Feature Elimination, Principal Component Analysis, and

Table. 2 Comparative Analysis of Selected Chest X-ray Deep Learning Studies

Ref.	Authors	Dataset	Technique	Models	Accuracy (%)	Transfer Learning	Strengths	Limitations
[1]	Anjali Panwar, Aman Dagar, Vikrant Pal, and Vinod Kumar	Not clearly specified	Custom CNN	CNN	~96.2	No	Lightweight and fast	No transfer learning; dataset vague
[2]	Heng Lu, Surangika A. Hewakankanamge, and Yiyu Miao	NIH ChestX-ray14, COVID-19	Transfer learning	VGG16, InceptionV3	~91–94	Yes	Domain adaptation	Real-world generalization
[3]	O. R. Devi, M. Kalyani Mayee, and S. Aarathi	Kaggle (COVID-19 & Pneumonia)	Transfer learning	DenseNet201, ResNet50	~94.5	Yes	Dual classification	Lack of interpretability
[4]	K. Selvi and D. Radha	Kaggle Pneumonia	CNN	CNN	~93.7	No	Simplicity and performance	No model comparison; lacks adaptability
[5]	Nidhi Gianchandani, Ankit Jaiswal, and Divyanshu Singh	COVIDx, ChestX-ray14	Ensemble Transfer Learning	DenseNet121, ResNet50, InceptionV3	97.89	Yes	High accuracy; ensemble strength	High computational cost
Our Study	Vaishnavi, Satya Prakash Singh	The National Institutes of Health (NIH) and Chest X-rays from the Guangzhou Women and Children's Medical Centre	Ensemble Learning	CNN-GRU model	98	Yes	High Accuracy	Need more data set for comparison

Autoencoders, which collectively optimize the feature selection process. Such approaches not only improve accuracy but also streamline the diagnostic workflow, catering to the increasing demand for efficient healthcare solutions. Furthermore, the promising accuracy rates demonstrated by the CNN-GRU model, particularly in distinguishing between healthy and diseased lung conditions, underscore its utility in real-world applications, aligning with contemporary needs for rapid and reliable diagnostic tools. Ultimately, this research contributes to the wider dissemination on utilizing artificial intelligence in medicine, open the way for future advancements that could revolutionize how lung diseases are detected and managed

The CNN-GRU model exemplifies a significant advancement in the integration of convolutional and recurrent neural networks, effectively addressing the complexities of spatiotemporal data analysis. This architecture leverages the strengths of CNNs in extracting spatial features from visual or auditory inputs, while GRUs adeptly handle the temporal dependencies inherent in sequential data. As highlighted in various studies, such a model not only enhances action recognition rates by a notable 14% but also demonstrates impressive performance in audio tagging tasks, achieving a state-of-the-art equal error rate of 0.12. The versatility of the CNN-GRU model positions it as a powerful tool across diverse applications, ranging from surveillance to smart home technology, further emphasizing the necessity for continued research and improvement in hybrid neural network methodologies. Ultimately, this model represents a promising frontier in machine learning, merging observational acuity with temporal understanding for more effective data processing.

The amalgamation of Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) for lung disease detection has implemented beneficial results, showing improved accuracies on multi class pulmonary findings. This hybrid approach has shown good effectivity by combining the strengths of CNNs for the extraction of features from imaging data with the sequential data modeling ability of GRUs to analyse time-series data, especially relevant to disease monitoring over time. Initial studies have demonstrated the

CNN-GRU structure to outperform conventional methods for classification and has also shown a lower number of false positives, which is important in a clinical context. Future research should aim to expand the application of the model, specifically on lung diseases but also including other disease areas and/or utilize more multimodal data that encompasses genomic or clinical data. Additionally, refining the model to allow for real-time diagnostics could enhance its overall usefulness and bring technology and clinical use closer together in the field of pulmonary health.

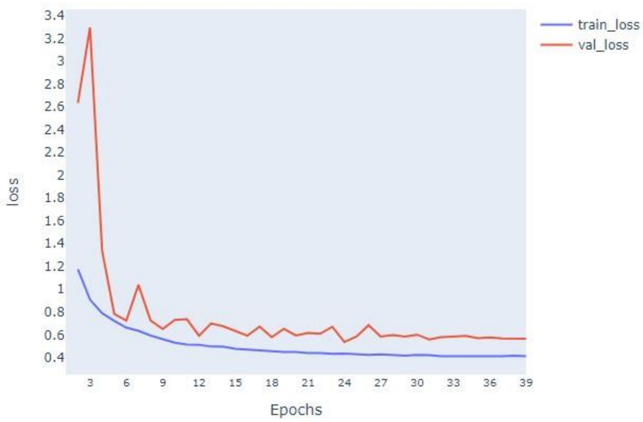

Fig.4 Training and validation accuracy curves

The CNN-GRU model describes a notable evolution in the realm of artificial intelligence, particularly in processing sequential data where spatial hierarchies and temporal dynamics are both essential. By integrating Convolutional Neural Networks (CNNs) with Gated Recurrent Units (GRUs), this model adeptly captures features from high-dimensional inputs, such as images or videos, while also managing temporal dependencies inherent in time-series data. This dual capability enhances performance in a variety of applications, including natural language processing, video analysis, and speech recognition, where understanding context over time is crucial.

The CNN component excels at extracting spatial features, while the GRU addresses the complexity of sequential information, allowing for more nuanced interpretations of data. Consequently, the CNN-GRU model not only advances accuracy in AI systems but also broadens their applicability, making it a vital tool for tackling complex real-world problems across multiple domains.

REFERENCES

1. A. Panwar, A. Dagar, V. Pal, and V. Kumar (2021), Pneumonia and Other Disease Classification using Chest X-Ray Images, 2021 2nd International Conference for Emerging Technology (INCET), 1–4.
2. H. Lu, S. A. Hewakankanamge, and Y. Miao (2020), Transfer Learning from Pneumonia to, 2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), 1–6.
3. O. R. Devi, M. K. Mayee, and S. Aarathi (2022), Identification of and Pneumonia in X-Ray Images using Transfer Learning, 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), 1–8.
4. K. S. and D. Radha (2021), Analysis of and Pneumonia Detection in Chest X-Ray Images using Deep Learning, 2021 International Conference on Communication, Control and Information Sciences (ICCISc), 1–6.
5. N. Gianchandani, A. Jaiswal, D. Singh s(2020), Rapid Diagnosis Using Ensemble Deep Transfer Learning Models from Chest Radiographic Images, Journal of Ambient Intelligence and Humanized Computing. https://doi.org/10.1007/s12652-020-02669-6
6. M. M. Alshmrani, Q. Ni, R. Jiang, H. Pervaiz, and N. M. Elshennawy (2023), A Deep Learning Architecture for Multi-Class Lung Diseases Classification Using Chest X-ray (CXR) Images, Alexandria Engineering Journal, 64, 923–935.
7. S. Kim, B. Rim, S. Choi, A. Lee, S. Min, and M. Hong (2022), Deep Learning in Multi-Class Lung Diseases Classification on Chest X-ray Images, Diagnostics, 12(4), 915. https://doi.org/10.3390/diagnostics12040915
8. Y. H. Bhosale and K. S. Patnaik (2023), PulDi-COVID: Chronic Obstructive Pulmonary (Lung) Diseases with Classification Using Ensemble Deep Convolutional Neural Network from Chest X-ray Images to Minimize Severity and Mortality Rates, Biomedical Signal Processing and Control, 81, 104445.
9. S. Bharati, P. Podder, and M. R. H. Mondal (2020), Hybrid Deep Learning for Detecting Lung Diseases from X-ray Images, Informatics in Medicine Unlocked, 20, 100391.
10. R. S. K. Boddu (2019), Lung Disease Detection Using Deep Learning Models: A Comparative Analysis, Journal of Cardiovascular Disease Research, 10(4)

AUTHORS

Vaishnavi received her BCA degree in computer science application from Birla Institute of Technology, Mesra, Ranchi, India in 2018 and her MCA degree in computer application from Birla Institute of Technology, Mesra, Ranchi, India in 2021. She is currently pursuing PhD at the Department of Computer Science and Engineering, Birla Institute of Technology, Mesra, Ranchi, India. Her areas of interest are artificial intelligence, machine learning, deep learning, and human disease detection by using artificial intelligence, machine learning, deep learning.
Corresponding Author E-mail: vaishnavi.ranu.123@gmail.com

Satya Prakash Singh is presently working as an Assistant Professor (Selection Grade) in the Department of Computer Science & Engineering, Birla Institute of Technology, Mesra, Ranchi, India. He has 23 years of teaching experience. He received his Ph.D. degree in Computer Science and Engineering in 2012. He has received an M. Tech. degree in Computer Science & Engineering in 1999. He received an M. Sc. Physics (Electronics) degree in 1997. He has supervised several research scholars of MCA, MTech and Ph D degrees. He has published more than 65 research papers in Scopus-indexed journals; IEEE, Springer, and Elsevier conferences, and many other national and international journals and conferences. He has been an editorial and reviewer in the Journal of Green Computing (Index in Scopus). His areas of interest include artificial intelligence, Data Mining, and Image Processing. Parallel and Distributed Computing, and Software Engineering. E-mail: sp.singh@bitmesra.ac.in